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Abstract: Automatic Identification System (AIS) transponders are used to identify and locate traffic. By recording AIS data, in a marine setting, it is possible to observe precise ship movements. An AIS-based maritime data modeling method is developed using a potential fields based method for extracting traffic patterns and detecting anomalies. The three aspects of potential field theory: charge accumulation, potential dissipation and field decay, enable the modeling of vessel traffic. STRAND, the tool visualizing the potential fields, shows actual past and present traffic behaviors and may generate traffic rules spontaneously. This study demonstrates and compares the modeling and detection results from three different areas, depicting a group of traffic rules identified in course of the result analysis. Based on the visual display of past traffic patterns, future routes may be optimized, using potential fields as a way of planning the actual route to destination. When deployed, such a solution could benefit a wide audience, from ship navigators, through traffic management, to transportation regulatory institutions.

1 INTRODUCTION

Decisions regarding detection of abnormal behaviors in maritime traffic are mainly taken on the basis of a human expertise. The operator that keeps track of the vessel movements has to monitor the open sea and harbors in order to detect suspicious behaviors and critical situations often in conjunction with available technical and automated systems to support the operators.

Just like road traffic, the marine traffic tends to concentrate locally in certain areas. The distances between ships tend to be smallest in harbors and river systems and largest on open sea. As a result, in some areas the traffic is precisely regulated, while in others it is less restrained. The demands for increased security can be addressed by increasing the surveillance capability and by proactively working to minimize the impact from threats. Much of what occurs in the maritime domain is also difficult to observe and assess with respect to vessel movements, activities, and intentions. There is a need to make the best possible use of all available data in order to detect and visualize out-of-the ordinary behavior.

Automatic Identification System (AIS) transponders are used to identify and locate traffic at the sea and in the air by electronically exchanging data with other nearby ships and airplanes and fixed receiving stations. These data give a lot of information about current traffic, such as position, course, speed, time of day and type of vessel. By recording AIS data, in a marine setting, it is possible to observe precise ship movements in e.g., a narrow waterway and hence to get an indirect view of the process of piloting.

In broad definitions of security, the prediction of what is yet to occur is always a vital aspect. Here, the typical behaviors, expected to happen in the future are defined using past traffic records. All collected AIS data is analyzed with the use of the
adapted potential field concept for data abstraction and representation. The intention of this study is to develop a maritime data modeling method that enables the extraction of traffic patterns and the anomaly detection. The general idea in applying potential fields for maritime traffic is, for the observed movement of each vessel, to assign charges along its track. A collection of charges distributed over an area generates a potential field, which is locally weaker or stronger depending on the density and strength of surrounding charges.

A normal behavior is an activity or state, which the collected dynamic data recognizes as something earlier detected by the AIS system according to time, space, speed, course, etc. Also, these values should not stand in contrast to the collected traffic data for a certain period of time. An anomalous behavior is a dynamic phenomenon changing over time not necessarily representing an emergency situation. It could be a novel detection not visible before by the system because of lack of collected data or detected data that stand in contrast to earlier collected data. In that perspective, the developed method subscribes to another branch of detection domain – namely, the novelty detection. The implication of anomaly detection using the potential fields method is that there is no final state or “perfect map” of the surroundings. Also a lot of false positives, i.e., novel incidents which in fact do not threaten traffic safety or require intervention, are necessary to be checked out for finding, the few, real anomalies in terms of emergency situations. This makes it difficult to validate the efficiency of the system, in the perspective of finding a once and for all anomaly detection.

This study may be regarded as opposite to expert systems, by reversing the process of detection. Anomalous behavior should not be defined directly, but implicitly — as a deviation from normal behavior by analyzing a large amount of data. This is a process similar to Google flu trends, where the presence of flu-like illness in a population is analyzed. Google Flu Trends monitor users’ health tracking behaviors online, i.e., the suspected anomalous behavior, and compares these findings to a normal level of influenza activity.

One of the aims is to improve understandability and maritime situational awareness, by visualizing the potential fields using modern rendering techniques. This would provide the maritime operators with a form of automated incident warning and analytical help in identifying traffic situations that merit further investigation.

Contrary to a sea chart, no background data such as obstacles and the sea shore is available for extracting traffic patterns using potential fields. The tool visualizing the potential fields starts with a “blank sheet” filling it with potential data from the AIS, i.e., making the obstacles “visible” by the lack of data instead of a pre-drawn template. This presents a possible double advantage. Firstly, the sea chart is constructed from the actual condition, e.g., a recently sunken wreck may easily be notified by the potential fields as a lack of traffic in that area. Secondly, the potential fields may generate traffic rules spontaneously. Normally, real security-related threats are difficult to find because such data are very irregularly available in the data set. Instead, rule confirmation will act as a corroboration of the method, i.e., both rule detection and generating anomaly patterns are the same kind of outcome ensuring a lowest common denominator.

Previous studies of potential field based modeling of traffic data, as well as the (based on it) anomaly detection, have demonstrated the applicability of the method and investigated its performance. Quite surprisingly, this method was also found to result in often characteristically asymmetric traffic patterns, which indicated an underlying rule in the traffic. Namely, in some areas ships deviating from their course to the left are considered to be more anomalous than if they deviated to the right. In other areas, traveling with speed higher than the locally most common speed is less (or in other cases – more) anomalous than slowing down to the next slower speed range. Under closer examination, and cross checking with the type of area being examined, it became apparent that the character of the perceived irregularities and asymmetries is very deterministic, and it seems to follow either man-made traffic rules or regular practices in sailing, commonly known by sailors, but not formally grasped or defined. The implementation of the method in form of a modeling and detection system STRAND, will be further shown in this publication, to deliver results allowing to grasp and clearly define regularities and rules in the maritime traffic.

The rest of the paper is organized as follows. Section 2 presents the background of self-learning anomaly detection decision systems based on different techniques such as machine learning, AI or statistics. In section 3 a traffic modeling and detection system, STRAND, is presented. The main results regarding anomaly detection and generating traffic rules are presented in section 4. Finally a
discussion and a summary of the major findings conclude the paper.

2 BACKGROUND

A problem within the maritime domain is the sheer amount of data that has to be processed. Advanced, self-learning anomaly detections are typically built on some form of machine learning, i.e., the study of algorithms that learn in some sense [10]. The algorithm is presented with a set of input data to be used to classify new input data (in the case of anomaly detection typically into the classes: anomalous and normal) and to predict how a modeled system will behave in the future.

There are two machine learning paradigms in particular that are suitable for developing this type of self-learning anomaly detection systems: unsupervised and supervised learning [11]. If the historical data (the input) is associated with correct classifications or predictions (the output), we may apply supervised learning algorithms to generalize from data with known classifications. If, on the other hand, we only have access to historical data without any associated predictions or classifications, we instead need to apply unsupervised learning techniques such as clustering [11]. Thus, for a classification problem, an unsupervised learning algorithm automatically partitions the data into groups while a supervised learning algorithm instead generalizes from data which has already been partitioned into groups.

In our AIS case, we do not know of anything unfavorable taking place in the observed time frame, so our approach (as is often the case in anomaly detection) is somewhere in between supervised and (fully) unsupervised learning, with our classifier learning normal behavior from our given example, but having no well formed idea about unwanted behavior as such.

The easiest way to track anomalous behavior given the described conditions is by identifying the absence of normality, i.e., studying models of maritime traffic, representing normal traffic behaviors. Ristic et al. [1] applied statistics to extract normal behavior patterns from primary data and consequently anomalies as lack of recorded motion relevant to normal trajectories and velocity. Riveiro and Falkman [4] combined user interaction with visualization techniques to obtain rule-based anomaly detection. Riveiro et al. [5] combines a visual approach (self-organizing maps) with nonparametric statistics (density estimation by Gaussian mixture modeling) and probabilistic theory (Bayes theorem).


Potential fields, not previously used for anomaly detection, were developed in the AI community as a navigation and decision making mechanism mainly for the development of game AI. The potential fields applied here to model maritime traffic are analogous to actual physical phenomenon of potential fields, e.g., electrostatic or gravitational [8], and are described in a similar manner. The three main concepts derived from the physical potential fields are the charge accumulation, the decay of potential fields, and the distribution of potential around a charge.

Each vessel tracked by AIS is characterized by a collection of static parameters, (e.g., name, flag, type), as well as the current state of its dynamic behavior (e.g., speed, course, location). The total charge at a location is calculated as the sum of all local charges, i.e., the greater an electric charge is, the stronger the electric potential field that surrounds it. A higher potential field indicates visits by more vessels at a location.

A field decay effect enables maritime traffic to evolve over time, i.e., to compare and follow trends of the changeable maritime traffic behaviors over time. It is an alternative to other constructs dealing with the real time continuity, such as a sliding time frame or a data window [1,9]. The field decay is here implemented as an exponential decrease of the charge. The prototype builds a normal model based on a real world AIS data set spanning 20 days. Each local charge gives rise to a local potential, most intensive in the location of the charge and dissipates with increasing radius. A global potential field is instantiated by merging local charges. The intensity of the field varies depending on the strength of the surrounding local charges and the distance to them.

The general idea of the proposed method, applying potential fields to maritime traffic, is for the geographical traces of vessel movements to assign charges to all passed locations. A collection of charges distributed over an area generates a potential field, which is locally weaker or stronger depending on the density and strength of surrounding charges. The three main concepts are the total strength of a local charge, the decay of potential fields, and the distribution of a potential
The strength of a charge \( c \) is a metric nearest to the AIS surveillance data (eq. 1). Each vessel tracked by AIS is characterized by a collection of numerical and verbal properties including vessel’s static parameters, (e.g., identification number, call sign, name) as well as current state of its dynamic behavior (e.g., speed or course).

\[
C_{lat, lon} = \left\{ c_{lat, lon}^1, c_{lat, lon}^2, \ldots, c_{lat, lon}^n \right\} \tag{1}
\]

The total charge \( C \) at a location \((k, l)\) is counted as the sum of all local charges \( c \) accumulated over a time period (eq. 2). The more vessels visits are reported in a location, the higher potential builds up in it, and around it.

\[
C_{lat, lon} = \sum_{i=0}^{r} c_{lat, lon}
\tag{2}
\]

The potential field formed by a single charge is strongest at the location of the charge, and dissipates within a radius around it. Areas where a potential is very strong represent a traffic pattern and belong to the model of normal behavior. On the other hand, areas where a potential is very weak or none, signalize absence of normal behavior, and therefore – anomaly. In this study the anomaly levels are determined using minimal potential thresholds (eq. 3). The total potential at location \((k, l)\) is the superposed potential generated by all surrounding charges in locations \((i, j)\), decreased by the distance between these locations. Here the potential distribution \( P \) is described by two-dimensional Gaussian smoothing, using Euclidean distance for measuring the radius between two points.

\[
P_{lat, lon}(t) = \sum_{i=0}^{r} \sigma \frac{1}{2\pi \sigma^2} e^{\frac{-\left(\text{lat}_i - \text{lat}_t\right)^2 + \left(\text{lon}_i - \text{lon}_t\right)^2}{2\sigma^2}}
\tag{3}
\]

It is desirable for the potential fields modeling maritime traffic, to evolve over time and reflect real-world traffic patterns changes. Instead of addressing the continuity of real time by applying constructs such as sliding time frame or data window [1,9], in this investigation a field decay factor is used (eq 4). It enables to continuously update and retrain the model by representing charge at a location as a function of time:

\[
C_{lat, lon}(t) = \sum_{i=0}^{r} d(t) c_{lat, lon}^i
\tag{4}
\]

where \( d(t) \) is a non-increasing decay function with limit at zero, describing the decrease of a local charge over time.

3 STRAND

A maritime traffic modeling and detection system STRAND (Seafaring TRansport ANomaly Detection) computes and displays distinctive traffic patterns as potential fields, extracted from the maritime surveillance data. In the AIS-based maritime surveillance case, static parameters for the vessels (identification number, call sign and name) as well as current state of its dynamic behavior (course, speed, time of day, location) are collected. STRAND further discretizes course and speed. Course is divided into 8 equal intervals: N, NE, E and so on. Speed ranges are not equal in size, and correspond to the speed classes common in maritime circles, ranging from Static (0–1 knot) Very slow (1-7), Slow (7-14), Medium (14-22), Fast (22-30), Very fast (30-45), Ultra fast (45-60), to exceeding 60 knots. The time of day divides 24 hours into four equal time slots: Morning (6–12), Afternoon (12–18), Evening (18–24), and Night (0–6).

![Figure 1. STRAND user interface; example of traffic patterns and detections in the open sea area.](image)
The technical limitation for tracking data update period is 90 seconds. Depending on the vessels movement the change in position will be less than 100 meters (speed limited to single knots in harbor and river areas) or close to 1000 meters (average speed of 20 knots in open sea) [7].

Besides using the aforementioned parameters, the STRAND system requires setting a grid size for the potential field. The grid size in essence defines the resolution of the potential map. It has been shown, that this parameter has a direct impact on the number of detected anomalies, and if set improperly may strongly overfit or underfit the data. I.e., on one hand, the number of suspected waypoint anomalies decreases when the grid size is enlarged, on the other hand bigger grid size might exclude real anomalies. A reasonable ratio, which minimizes the amount of false anomalies without excluding any real deviation, needs to be found.

A charge multiplier was introduced as a compensation for the imbalance between the amounts of charges generated by vessels traveling with different speeds. All components of a single charge set, representing one AIS message, were multiplied by the square root of the vessel speed. A Web-based prototype system was implemented using the Django Python Web framework.

The STRAND user interface includes a map with overlays (from Google Maps API v3) and a set of controls, see figure 1. The controls include menus for setting the coordinate limits, potential metric and range of the metric value, as well as the optional time frame. The potential intensity is represented by heat maps, where the color palette ranging from green, yellow to red, represents increasing potential values.

In the figure, the small black arrows represent vessels conforming to the normal behavior patterns, and all anomalously behaving vessels are marked by larger red arrows. So, a red arrow indicates a vessel outside the potential field of at least one type, e.g., navigating in a wrong direction. Also an abnormal speed or time of day may indicate an anomalous behavior.

Besides the shown open sea area, two other areas are chosen for investigation: the estuary of the Oder River along with the bay of Szczecin representing the river case (figure 2), and the harbor case of the Gdansk bay with ports of Gdansk, Gdynia and others (figure 3). The shown open sea area between Sweden and Poland in the Baltic Sea (figure 1) covers two main routes outside the east coast of Sweden, each represented by a double line. The red color indicates a strong potential field with traffic in two directions, NE and SW. At the bottom of the folded open sea, are the increased potential fields indicating close proximity to the bay of Szczecin, i.e., traffic to and from the harbor of Gdynia and Gdansk.

4 ANOMALIES AND GENERATED RULES

The potential field based method, implemented by the STRAND system, produces different results, based on the specific scenario settings. Each potential field is specific to one AIS metric (i.e., waypoint, speed, course or daytime). The geographic area, in which to aggregate charges and distribute potential, is delimited by two pairs of latitude and longitude bounds. The time selection is necessary for limiting the traffic records, based on which the fields are created, as well as to determine the moment in traffic that should undergo the anomaly detection. Additionally, a classification threshold is set to draw a line between the anomalous and normal potential levels.
All of the above parameters are constant throughout the experiments in this study. I.e., the time frame, detection moment, and detection threshold remain the same. The three selected areas have unchanged bounds, and for each of them a complete set of all potential fields is built and used for detection.

The focal point is the grid size influencing the resolution of the vessel traffic model. A larger grid size means a lower resolution, and if increased too high, may cause under fitting the underlying traffic patterns, and exceedingly lowering the sensitivity. On the other hand, high-resolution grids may result in over fitting the model and making the detection too sensitive.

By visualizing the potential fields a human expert may get an overview of the past and present traffic. This is not similar to an ordinary visualization of the AIS data where the current traffic situation is monitored. This difference is illustrated by the example below where ships seem to get closer to the opposite riverbank either to dock or to cut the turn. On the other hand, the north-eastern traffic seems to keep to the right bank in the south, but gets somewhat diffused towards the mouth of the river.

The distribution of the potential also allows observing a probable reason for that NE traffic diffusion. A point at the western riverbank in the middle of both images appears to be a frequent destination for tracked vessels, some of which seem to show disregard to traffic rules when departing in north-eastern direction. That behavior occurred often enough to build up a relatively strong traffic pattern, and if repeated - it will be concerned normal from a course specific point of view. If speed, daytime and type of ship are evaluated, new anomalies may occur.

The potential field based method may act as a way of finding unexpected behavior, i.e., anomalies and monitoring normal behavior, i.e., finding actual rules. Later on, in the discussion part, these findings together with the choices made by a human expert may result in an extended analysis of ship navigation.
4.1 Anomalies

Figure 5. Percentage of anomalies for different grid sizes.

Figure 5 displays anomaly detection statistics for maritime traffic as a function of grid size. The plot represents the numbers of detections of types: waypoint, course, speed, daytime and total. The total is a sum of all positive detections regardless of type where course, speed and daytime are detections made separately for these parameters. The specific detections may overlap, e.g., a ship may travel with anomalous course and time of day, but at a speed that is normal for its location. The waypoint detection is triggered when a vessel is observed in an area not earlier investigated by a vessel. As a consequence this type of anomaly also indicates anomalous speed, course and daytime, i.e., provide multiple anomaly values.

In practice the STRAND system recognizes the waypoint detections as a deficit of any manner of recorded vessel present at an examined location. The observed tendency is that for oversensitive detection settings (where the grid is too dense), the proportion between the general (waypoint) and specific detection (course, speed, daytime) is strongly skewed towards the former type. The reason being that in a small size grid the distances between waypoints recorded in fact relatively close to one another, are so many grid nodes apart, that they cannot create a common potential field (i.e., a traffic pattern).

In figure 6, the waypoints (solid lines) represent a lot of anomalies for small grid sizes, especially at open sea. If we can find a local optimum for an investigated specific parameter this is a “worst case” scenario regarding the number of found anomalies for a certain attribute. If this also is correlated to fewer anomalies connected to the general, waypoint, parameter, a possible grid size candidate is found. The decline in the number of anomalies is much faster for the harbor and especially the river cases which suggest using a smaller grid size for these cases.

Both course and speed reaches a peak around the grid size 600 - 800 m for the open water case at the same time as the number of waypoint anomalies get reasonable low in number. For the harbor case there is a similar peak around 60 - 80 m grid size where the peak of the river case is between 30 – 100 m but with fewer anomalies. Both open sea and harbor detects around 25% possible anomalies where the river case holds less than 10% alarms for course deviations. Also for speed deviations there is a higher percentage for the open sea (20%) than for the harbor and river cases (below 10%).

So, by plotting transmitted waypoints it is possible to detect previous positions and the proportion of vessels that visited the same waypoints in the past. With larger grid sizes the number of anomalies decreases, especially in dense areas with heavy traffic. In the same way, by plotting courses and speed it is possible to detect more volatile changes in the positions done by the vessels. This entirely sum up to different anomaly detections; one exclusively for waypoint and one partly overlapping for course and speed, i.e., a human observer needs to evaluate different cases of anomalies.

4.2 Traffic rules at Sea

Besides the already mentioned parameters, added sets are produced by performing detection on data with altered speed and course. For speed, the velocity may increase or decrease relative to the current speed. As seen in figure 7, the chosen grid size is important and dependent on where the vessels are in the sea, e.g., how close to the shore, and the
conditions imposed by this position, e.g., density of vessels and possible or allowable speeds. In the following examples we have chosen a grid size of 30 meters for the harbor and river cases and 800 meters for the open sea case.

Figure 7. Speed limits for open sea, harbor and river cases.

Changing speed is raising the percentage of anomalies for all investigated areas. For two of them, harbor and river, the amount of anomalies are quite low for the investigated speed but an increase in speed multiplies the amount of anomalies compared to driving with normal or decreased speed.

For the open sea the initial amount of anomalies are higher, about 10 times higher than for the harbor and river cases. In contrast to these cases it is a more unexpected behavior to drive slower than to increase the speed or keep to the original speed.

From our general understanding this is not a surprise. Harbor areas as well as river paths have speed limits depending on narrow passages and dense traffic. Anomalies that normally constitute a few percent for normal and low speed may induce more than 50 percent of all traffic with increased speed for the harbor case. For the open sea the opposite is true, do not reduce speed or stop. This unexpected situation is handled as an emergency situation at sea when the vessel is stopped. So, reduce the speed is a sign of an anomaly behavior.

The next case, turning left and right given a proposed course, was preceded by two additional tests. The first test has to do with granularity, is it better or not to make a large adjustment? We compared 45 to 22.5 degrees, e.g., turning NE instead of NNE. Finer granularity moderately increased the number of anomalies without changing the overall results. The second test adjusted the initial setting for the horizontal direction, e.g., adjusting from N to NNW, to find the optimal setting. Only small adjustments were measured depending on this shift in direction, i.e., the STRAND tool seems to be robust against this kind of adjustment.

For the investigated grid size the deviations from course are less apparent than for the speed parameter as seen in figure 8. Rivers are similar to highways on land, elongated routes where the ships hold a definite direction. River has a deviation to the left resulting in a 50% increase of anomalies for a grid size up to 60 meters. The deviation to the right is almost the same as the original number of waypoint anomalies. Harbors have less determined routes depending on traffic to and from the quays. For the harbor case there are no detected differences between left and right but an overall 50% increase of anomalies compared to the original waypoint deviation.

Open sea has a slightly deviation towards right (around 10%) but also a large increase of anomalies compared to the original waypoint deviation (above 100%). This may be regarded as too many detection of anomalies due to the large grid size (700-1000 m).

So, traffic rules have partly been discovered when introducing potential fields comprising; upper speed limits, abrupt braking and right rule:

- Upper speed limits are significant for both harbor and river situations. This is consistent with the actual situation at sea where speed limitations often are present in these areas. In harbor and river areas speed is regularly limited by law, obstacles and (or) sailing practice, therefore exceeding it is more dangerous and less common than slowing down even more.
- At open sea it is common to sail with particular minimal speeds, and exceeding them is not disadvantageous. Slowing down speed at open sea may result in a potential stop impeding the
traffic. This is consistent with maritime rules where an unexpected situation is handled as an emergency situation at sea, e.g., hoist a black orb in the mast, when the vessel is stopped.

- Traveling along a river is similar to traveling on a motorway, the driver needs to follow traffic rules, in this case the right rule. The generated potential fields discover this rule automatically; avoid shifting towards oncoming traffic, i.e., turning left.

5 DISCUSSION

An extended analysis of ship navigation and its actual practice aboard large ships in a naval setting has been studied by Hutchins [13]. This study involves distributed ship navigation composed of multiple crew members, navigational instruments, water and environmental conditions. Cognitive skills observed in the actual practice aboard, referred to as cognition in the wild by Hutchins, constitute the human knowledge. The actual result, i.e., how the ship makes its way, is monitored by its AIS positions. Navigational skills are monitored and visualized by the concept of potential fields. So, distributed cognitive processes in a ship may partly be handled by potential fields because of the embedded cognitive skills in the AIS. The visualization takes into account strength and distribution of the potential field during a specific period of time. A decay function guarantees a flexibility over time; varying long term conditions affect the result by favoring newer measurements in front of older.

Findings regarding speed and right rule appear to correspond with common sense. Real anomalies in the context of causing accidents or being indicators for terrorist acts or smuggling are rare. We are instead investigating candidates for becoming a threat to the regular vessel traffic. Stated another way, a human expert may exclude all normal behavior and concentrate on the proposed anomalies. The introduced anomaly detection tool, STRAND, should be regarded as a visualization tool for a human expert, introducing some novel skills compared to traditional equipment like radar and GPS. The AIS vessel tracking data incorporates seaman’s experiences in estimating the changing traffic and operating environment conditions.

The concept of visualization may include finding both anomalies and rules of behavior outside the human expertise. Current tools that visualize the AIS system give an overview of encountered vessels in a given area, including e.g., type of ship, speed and position, the previous route and destination and also preferred behavior, i.e., seamanship. A perfect overview of the actual traffic cannot be guaranteed, e.g., some of the data must be inserted manually and the AIS equipment may deliberately or accidentally be out of service.

Adding visualization of the potential fields as a complement to the current AIS tools will improve the overview because it takes into account data of past experiences. Potential fields may act as a way of planning the actual route to destination. Waypoints may deviate and a certain velocity may be preferred depending on time of day, weekday and time of the year. By plotting transmitted waypoints it is possible to detect previous positions and the proportion of vessels that visited the same waypoints in the past. In the same way, by plotting courses and speed it is possible to detect more volatile changes in the positions done by the vessels.

Still there will be lots of false alarms, and most possible some real incidents not detected. For a supervisor, monitoring the actual traffic, introducing a tool for visualizing the potential fields may facilitate traffic surveillance. So, it is possible to optimize routes depending on past experiences, i.e., using potential fields as a way of planning the actual route to destination. Waypoints may deviate and a certain velocity may be preferred depending on time of day, weekday and time of the year. This may act as a planning tool subject to direct observations.

There are various potential benefits and practical applications of the method, depending on the user. From a ship navigator point of view, the display of patterns of correct or normal behavior, aids the choice of the safest and most optimal path. From traffic safeguarding perspective, the anomaly detection based on potential fields may help quickly and comprehensively inspecting possible traffic incidents. Finally, from authorities’ point of view, the clear overview of traffic may help recognize traffic regulation and legislation issues.

6 CONCLUSION

The STRAND prototype system demonstrates the applicability of the proposed method. The geographical map-based grid is filled by a potential field derived from the observed traffic. Anomalies are identified as a lack of normal behavior — local absence of potential. The three aspects of potential field theory: charge accumulation, potential decay
and dissipation; enable the modeling of vessel traffic. The resulting normal model facilitates customizable visualization and anomaly detection. An advantage of the method is the ability to create normal traffic models based on the traffic history, without the need for expert knowledge. The additional beneficial property demonstrated, analyzed and discussed in this study, is the ability to grasp behaviors common in the sailing practices in a way that can be easily expressed as a traffic rule.

7. REFERENCES

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